

## Spectral Reflectance as a Covariate for Estimating Pasture Productivity and Composition

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### ABSTRACT

Pasturelands are inherently variable. It is this variability that makes sampling as well as characterizing an entire pasture difficult. Measurement of plant canopy reflectance with a ground-based radiometer offers an indirect, rapid, and noninvasive characterization of pasture productivity and composition. The objectives of this study were (i) to determine the relationships between easily collected canopy reflectance data and pasture biomass and species composition and (ii) to determine if the use of pasture reflectance data as a covariate improved mapping accuracy of biomass, percentage of grass cover, and percentage of legume cover across three sampling schemes in a central Iowa pasture. Reflectance values for wavebands most highly correlated with biomass, percentage of grass cover, and percentage of legume cover were used as covariates. Cokriging was compared with kriging as a method for estimating these parameters for unsampled sites. The use of canopy reflectance as a covariate improved prediction of grass and legume percentage of cover in all three sampling schemes studied. The prediction of above-ground biomass was not as consistent given that improvement with cokriging was observed with only one of the sampling schemes because of the low amount of spatial continuity of biomass values. An overall improvement in root mean square error (RMSE) for predicting values for unsampled sites was observed when cokriging was implemented. Use of rapid and indirect methods for quantifying pasture variability could provide useful and convenient information for more accurate characterization of time consuming parameters, such as pasture composition.

SAMPLING IS THE researcher's best way to learn about a population. When a pasture is considered to be a population, the task is to determine where to sample and how to assess the true variability as accurately as possible. With only a limited number of observations attainable because of time and labor constraints, interpolation is necessary to estimate values at unsampled points.

Matheron's theory of "regionalized variables" (Matheron, 1971) reported that field variables can be spatially correlated, or coregionalized. Geostatistics is the field of study that models spatial variability and is used to predict unknown values in space (Journel and Huijbregts, 1978). Consequently, spatial correlation within pastures is an opportunistic reality. Webster et al. (1989) capitalized on this observation by designing a sampling scheme for ground-based radiometry measurements in both species-poor and species-rich grassland and winter barley (*Hordeum vulgare* L.). By fitting a semivariogram to radiation reflectance data sets, the error associated with

estimating unsampled points for varying sampling intervals and densities was calculated (Webster et al., 1989).

The reflectance data measured in the Webster et al. (1989) study was optimal in the sense that it was a spatially correlated variable that was rapidly and densely collected. In this study, data of multispectral canopy reflectance were used for similar reasons.

Multispectral reflectance measured with hand-held radiometers has been used to estimate many plant parameters of interest. Reflectance has been correlated with plant greenness in peanut (*Arachis hypogaea* L.) (Nutter, 1989; Aquino et al., 1992) and in maize (*Zea mays* L.) (Ma et al., 1996). Reflectance measurements were also found to be successful estimators of biomass in alfalfa (*Medicago sativa* L.) (Mitchell et al., 1990), peanut (Nutter and Littrell, 1996), and potato (*Solanum tuberosum* L.) (Bouman et al., 1992). Seasonal biomass changes in tallgrass prairies were modeled by the normalized difference vegetation index (NDVI) along with several other environmental variables (Olson and Cochran, 1998). Light reflectance before anthesis may be able to predict grain yield in corn (Ma et al., 1996), canopy reflectance measurement at pod setting stage in soybean aided in early prediction of soybean [*Glycine max* (L.) Merr.] yield (Ma et al., 2001), and a good correlation was found between NDVI and millet total dry matter at harvest (Lawrence et al., 2000).

Reflectance indices involving different wavelengths can also be used to discriminate between weed and crop species (Vrindts et al., 2002). Discriminant analysis in this study also resulted in 94% correct classification of broadleaved plants in test datasets of broadleaved plants and grasses (Vrindts et al., 2002).

Measuring pasture variability through the use of a ground-based multispectral radiometer can be performed quickly, nondestructively, and inexpensively. Consequently, canopy reflectance data on a dense grid can be easily obtained. This dense data collection can be capitalized on through the use of geostatistics. Kriging is a method of interpolation used when a variable displays spatial autocorrelation. Because reflectance values are spatially correlated (Webster et al., 1989), kriging can be used to predict reflectance at unsampled points. Cokriging is also an interpolation method used where there are two or more spatially interdependent variables. Often, cokriging is used when one or more other properties have been extensively sampled in comparison to the variable of interest (Oliver, 1987). Ideally, the densely sampled variable, termed a covariate, secondary variable, or subsidiary variable, is measured more cheaply and quickly than the property of interest, or target vari-

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**Abbreviations:** NDVI, normalized difference vegetation index; RMSE, root mean square error.

able. Therefore, canopy reflectance may serve as a covariate and noninvasively provide valuable and inexpensive information as a surrogate for prediction of other plant parameters of interest.

In this study, cokriging methods were compared with kriging methods for predicting measured plant parameters of interest. The objectives of this study were (i) to determine the relationships between easily collected canopy reflectance data and pasture biomass and species composition and (ii) to determine if the use of pasture reflectance data as a covariate improved mapping accuracy of biomass, percentage of grass cover, and percentage of legume cover across three sampling schemes in a central Iowa pasture.

## MATERIALS AND METHODS

The experiment was conducted during June 2001 at the Iowa State University Rhodes Research Farm (41°52' N, 93°10' W) in central Iowa. The field of study was a 0.42-ha nongrazed, grass-legume pasture. The dominant species included smooth brome grass (*Bromus inermis* Leyss), reed canarygrass (*Phalaris arundinacea* L.), Kentucky bluegrass (*Poa pratensis* L.), birdsfoot trefoil (*Lotus corniculatus* L.), and cicer milkvetch (*Astragalus cicer* L.). While there was mechanical removal of vegetation in early spring each year, the cool season grass-legume pasture had not been grazed in six years during a rotational grazing study. To avoid disrupting grass-legume balance, the pasture did not receive any fertilizer from 1996 to 2001. As an indication of field topography, the pasture site included topographically distinct summit, sideslope, toeslope, backslope, and opposite summit landscape positions. Slope ranged from approximately 1 to 9° and elevation ranged from 296.6 to 303.0 m above sea level.

A dense sampling grid consisting of 116 points was devised for the pasture. Sampling points were arranged in a triangular grid with inter- and intrarow separation distances of 6 m. To obtain data from samples located closer than 6 m, an additional point was sampled within each row at randomly chosen 1- or 2-m separation distances. An earlier study of the pasture site indicated short-range variation in soil characteristics such as soil P, K, pH, and organic matter (Tarr et al., 2003). As a result, this short-range variation in soil samples was investigated to obtain a more reliable experimental semivariogram model (Burgess and Webster, 1980; Kravchenko and Bullock, 2002). Each sampling point was georeferenced by GPS.

Canopy reflectance was measured at each of the 116 points on 8 June 2001. Grasses and legumes were in late vegetative-early reproductive stages. Canopy reflectance was measured with a handheld portable multispectral radiometer (CROP-SCAN, Inc., Rochester, MN, model MSR87) over the center of each 1-m<sup>2</sup> quadrat. Reflectance was measured at eight wavebands centered at: 460, 510, 560, 610, 660, 710, and 760 nm as well as a far infrared (IR) band from 1550 to 1750 nm. Bandwidths were approximately 10 nm for wavebands in the visible light and near infrared (NIR) regions (460–760 nm wavebands).

The circular field-of-view for the radiometer was matched as closely to the size of the 1-m<sup>2</sup> quadrat as possible. Reflectance was averaged over the area measured because the diameter of the field-of-view was equal to one half the height of the radiometer sensor above the plant canopy. Two radiometer measurements were made in rapid succession and averaged at each of the 116 points. Measurements were taken between 1130 and 1400 h daylight time to minimize the effects of sun angle on incident radiation (Guan and Nutter, 2001). A bubble

spirit level mounted on the support pole of the radiometer ensured that the radiometer sensors were parallel with the pasture canopy. There were few clouds, a sunny sky, and minimal wind on the date of measurement.

On 11 June 2001, species composition was evaluated. Using the Daubenmire canopy coverage method (Daubenmire, 1959), we ranked species within a 1-m<sup>2</sup> quadrat according to coverage abundance. Immediately following the ranking, the 1-m<sup>2</sup> quadrats were harvested with a mechanical hedge trimmer and cut as close to ground level as possible. Above-ground biomass was placed in forced-air drying ovens at 60°C for 48 h and then weighed to determine biomass for each quadrat. Elevation data were recorded with a Leica System 500 real time kinematic (RTK) system (Leica, Switzerland) and slope data were calculated from this by ArcView 3.2 Spatial Analyst (ESRI, 1996). Geostatistical analyses were performed by ArcView 8.1 ArcGIS Geostatistical Analyst (ESRI, 2001).

## Sampling Schemes

Three different sampling patterns of  $n = 30$  were created from the original dense sampling grid ( $n = 116$ ). The sampling schemes were a grid pattern, a triangular pattern, and a random scheme. The sampling schemes are shown in Fig. 1. Because the sampling schemes were created from the original sampling grid, there were some restrictions on the arrangement of the patterns. The grid pattern was a rectangular grid with 6-m intrarow and 12-m interrow separation distances. The sampling scheme originated on the west end of the pasture and because of the specified sample size, sampling density on the east end of the pasture was less dense. For similar restriction reasons, the triangular scheme is more dense on the east end of the pasture. The triangular pattern was not equilateral; the triangles were formed with a base length between points of 6 m and a side length of 19 m for nearly all of the pasture and 12 to 13 m on the extreme east end of the pasture. Lastly, a random number generator was used to produce a sampling scheme with size  $n = 30$  from the original 116 sampling points for the random sampling scheme.

Because plant measurements were taken at each of the original 116 sampling points, a relatively large validation set was available. Eighty-six points were used as an independent validation set for the  $n = 30$  sampling density.

## Equations and Data Manipulation

When analyzing reflectance results, the normalized difference vegetation index was defined as:

$$NDVI = \frac{NIR - red}{NIR + red}$$

Two variants of NDVI were calculated with different red wavebands. NDVI1 was calculated with reflectance at 610 nm and NDVI2 was calculated with reflectance at 660 nm.

Kriging and cokriging were performed by the Geostatistical Analyst extension in ArcView 8.1 (ESRI, 2001). Adequacy of the chosen variogram models was tested by cross-validation (Vauclin et al., 1983; Warrick et al., 1986). In a cross-validation, each point in the sampling scheme is removed singly and its value is predicted by kriging the remaining data. The resulting RMSE of the cross-validation process was examined, and the variogram model with the lowest RMSE was selected (Vauclin et al., 1983; Heisel et al., 1999). Skewness results indicated that not all the data were normally distributed. To improve normality, the reflectance data for the following covariates was log-transformed: 660 nm, the far IR band, and the NIR/Red1 ratio. In addition, the  $\sin^{-1}$  transformation was imple-

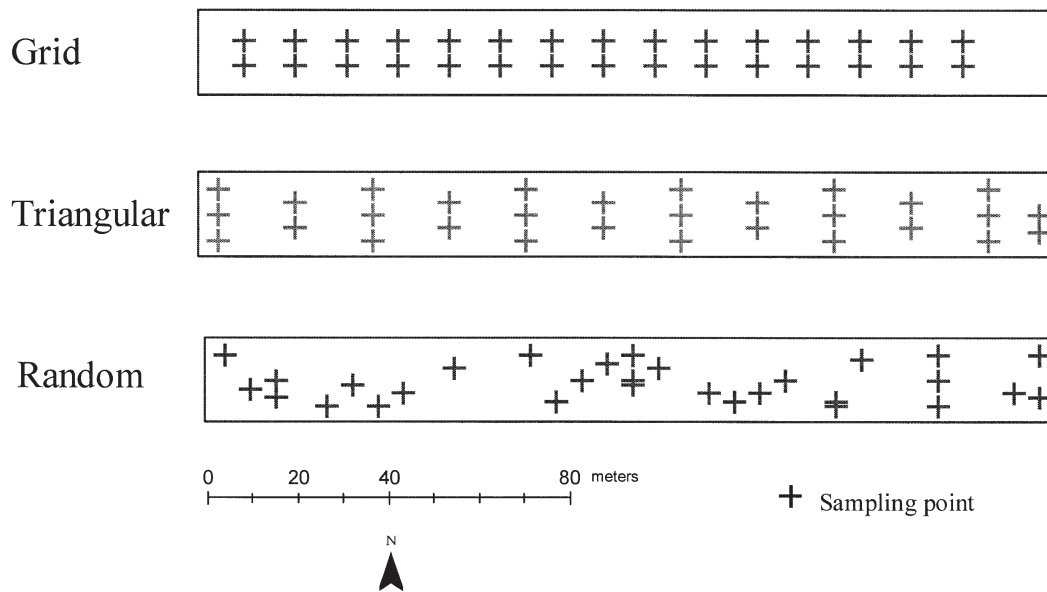


Fig. 1. Three sampling schemes at  $n = 30$  density.

mented for the NDVI1 and NDVI2 indices. Data were reported on the nontransformed values.

For both kriging and cokriging and for each sampling scheme, the root mean square error was calculated as:

$$RMSE = \left\{ \frac{1}{n} \sum_{i=1}^n [z(s_i) - z^*(s_i)]^2 \right\}^{0.5}$$

where  $n$  is the number of sample sites in the validation set,  $z(s_i)$  are the observed values, and  $z^*(s_i)$  are the predicted values.

Relative reduction in RMSE was defined by:

$$100(RMSE_k - RMSE_{ck})/RMSE_k$$

where  $RMSE_k$  and  $RMSE_{ck}$  are the root mean square errors of kriging and cokriging, respectively (adapted from Zhang et al., 1992).

## RESULTS

### Statistical Data Analysis

Summary statistics of pasture biomass and species composition values for the initial, dense grid ( $n = 116$ ) sampling scheme are presented in Table 1. Biomass had a large range in values; however, it had a relatively low CV. On average, the pasture was composed of more grass than legume species, with smooth brome grass as

Table 1. Descriptive statistics of measured plant parameters for 116 sampling points.<sup>†</sup>

	Mean	SD	CV	Minimum	Maximum
Biomass, g DM m <sup>-2</sup> ‡	463	91.3	20	226	704
Grass, %	85	16.1	19.0	33.9	100.0
Smooth brome grass, %	49	30.6	62.6	0	97.5
Kentucky bluegrass, %	7	8.6	118.4	0	39.5
Reed canarygrass, %	29	39.2	137.1	0	100.0
Legume, %	14	16.1	116.5	0	64.5
Birdsfoot trefoil, %	11	13.1	119.0	0	54.8
Cicer milkvetch, %	3	8.7	310.4	0	51.5
Other, %§	2	4.0	264.2	0	27.7

<sup>†</sup> Samples measured on 1-m<sup>2</sup> quadrats.

<sup>‡</sup> Biomass is above-ground plant material, percentage of plant cover assessed by the Daubenmire canopy coverage method (Daubenmire, 1959).

§ Indicates weed species.

the most abundant grass. Absence of each species was found at one or more of the quadrats, as indicated by the minimum percentage of cover. However, grass was always present within the quadrats. The large CVs for species composition indicated the high variability in species occurrence throughout the pasture. From a sampling perspective, this known variability is of interest because it is important that a sampling technique can identify this variability in its resulting map. Furthermore, management decisions are made based on this map. In addition, weed species were not particularly prevalent. The primary weed species were yellow nutsedge (*Cyperus esculentus* L.), common dandelion (*Taraxacum officinale* Weber), and yellow rocket (*Barbarea vulgaris* R. Br.).

The degree to which canopy reflectance values are spatially correlated with the plant parameters of interest is called coregionalization. Although statistical correlation does not imply spatial correlation, the dense data set in this study does suggest a baseline for spatial relationships to exist among the plant parameters. The relationships between reflectance values and productivity and species composition are shown in Table 2.

The results of the large data set indicated several significant relationships between measured plant parameters of interest and reflectance values. For example, values of  $r \geq 0.40$  were found between biomass and NDVI1, NDVI2, NIR/Red1 ratio, and NIR/Red2 ratio (Table 2). percentage of coverage of grass was correlated with reflectance in the far IR band and at 660 nm (values of  $r \geq 0.29$ ). Also, percentage of coverage of legume was correlated most highly with reflectance at 660 nm, 460 nm, and at the far IR band (values of  $r \geq |-0.27|$ ). These relationships were capitalized on by cokriging. The spectral wavebands most highly correlated with the plant parameters of interest were used as covariates.

The highly significant negative correlation ( $-0.97$ ) between percentage of grass cover and percentage of



**Table 2. Partial correlation matrix among plant and canopy reflectance parameters for 116 sampling points.**

	Grass	Leg.	Bio.	460	510	560	610	660	710	760	Wide	NDVI1	NDVI2	NIR/Red1	NIR/Red2	FIR/Red1	FIR/Red2
Grass, % <sup>†</sup>																	
Legume, %	-0.97 <sup>‡</sup>																
Biomass	-0.27	0.33															
460 nm	0.25	-0.28															
510 nm	0.19	-0.22	-0.21	0.96													
560 nm				0.61	0.73												
610 nm	0.20	-0.23	-0.38	0.80	0.91	0.75											
660 nm	0.29	-0.31	-0.40	0.74	0.81	0.38	0.88										
710 nm				0.65	0.74	0.79	0.46										
760 nm			0.30			0.40	-0.51	0.39									
Far IR	0.30	-0.27	-0.32			0.23	0.24	0.20									
NDVI1	-0.19	0.19	0.43	-0.37	-0.47		-0.64	-0.86									
NDVI2	-0.23	0.23	0.40	-0.39	-0.46		-0.59	-0.87	0.86			0.99					
NIR/Red1			0.43	-0.35	-0.47		-0.65	-0.84	0.85			0.98	0.95				
NIR/Red2	-0.19	0.20	0.40	-0.40	-0.48		-0.62	-0.86	0.85			0.98	0.97	0.99			
FIR/Red1				-0.65	-0.67	-0.35	-0.61	-0.66	-0.37	0.28	0.71	0.51	0.51	0.55	0.58		
FIR/Red2				-0.65	-0.66	-0.19	-0.62	-0.79	-0.24	0.50	0.63	0.69	0.72	0.72	0.77	0.95	

<sup>†</sup> Grass and legume measured by canopy coverage method (Daubenmire, 1959), biomass is above-ground plant material in g DM m<sup>-2</sup>, nm is nanometer, wide IR band is 1550–1750 nm, NDVI is normalized difference vegetation index calculated with Red1 (610 nm) or Red2 (660 nm), NIR is near infrared (760 nm), FIR is far infrared (1550–1750 nm).

<sup>‡</sup> The critical value for the 5% two-sided significance test is 0.18; correlations less than 0.18 are omitted.

legume cover indicated that the occurrence of the two vegetation classes was inversely related. In addition, because of the fairly narrow spectrum of wavebands used and relatively wide spectral resolution (i.e., bandwidth), the reflectance values in the visible light region (400–700 nm) exhibited strong colinearity as did the ratios using the two wavebands of red light (Table 2).

### Geostatistical Data Analysis

Interpolation is necessary to map a variable of interest at the ground from a sample of that variable. Kriging does this optimally in the sense that it estimates unsampled values with minimum variance. Both the theory and application of kriging are described in depth by Journel and Huijbregts (1978) and McBratney and Webster (1983a). We investigated the value of using one or more reflectance values or indices as a covariate for cokriging. Mapping accuracy of kriging the plant parameters of interest was compared with that of cokriging the plant parameters with reflectance values as a covariate.

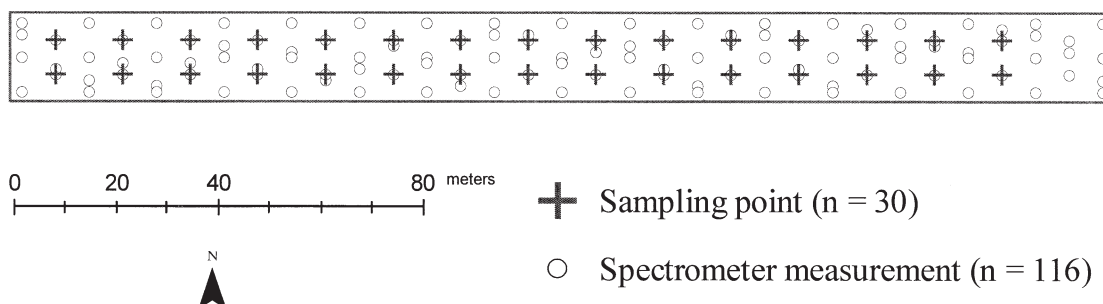
The pasture of study was oriented mostly in one dimension, and there were insufficient sample pairs of the plant parameters for the  $n = 30$  sampling scheme to obtain well-structured directional semivariograms (Trangmar et al., 1986). Therefore, it was assumed that all semivariograms were isotropic. Lag distances ranged from 3 to 16 m with the majority of values being 8 m. Lag distances were autocalculated by the ArcView 8.1 Geostatistical Analyst extension (ESRI, 2001). This method

tries a series of lag values, with their size increasing in a geometric sequence. Geostatistical Analyst then looks through all the lags and finds the lag and set of variogram parameters that have the “best fit,” or smallest weighted least squares (J.M. Ver Hoef, Alaska Department of Fish and Game, personal communication, 2002).

The three plant parameters of interest, above-ground biomass, percentage of grass cover, and percentage of legume cover, were undersampled compared with the canopy reflectance readings. This is the situation where cokriging is most useful. Because of the ease of collecting dense, rapid, and georeferenced canopy reflectance data, its spatial relationship with the three plant parameters was explored. In this 0.42-ha pasture, canopy reflectance at 116, 1-m<sup>2</sup> quadrats was measured. Consequently, the ratio of sampling intensities of reflectance to the other plant parameters was nearly 4:1 for the  $n = 30$  scheme (Fig. 2).

To apply cokriging, it was necessary to model semi-variograms for each plant variable separately as well as cross-variograms for all pairs of canopy reflectance and plant parameters measured at the same location (McBratney and Webster, 1983a, 1983b; Vauclin et al., 1983; Triantafyllis et al., 2001). The correlations shown in Table 2 were also examined (Chien et al., 1997). Proof of some level of coregionalization between canopy reflectance and the three plant parameters of interest was important for further cokriging steps.

One, two, and three covariates were examined to



**Fig. 2. Map of plant sampling points and spectrometer covariate points.**

determine if using more than one covariate improved cokriging prediction accuracy (McBratney and Webster, 1983a). One covariate,  $\sin^{-1}$  transformed NDVI1, was optimal for biomass as there was difficulty computing the covariance matrix for two and three covariates in the grid and triangular schemes. Cokriging with the log-transformed far IR and log-transformed 660-nm wavebands was optimal for cokriging with percentage of grass cover. Three covariates, log-transformed 660 nm, 460 nm, and the log-transformed far IR band, were optimal for percentage of legume cover. Covariate selection was determined on the basis of correlation with the plant parameter of interest (Table 2). The minimization of kriging RMSE for cross-validation sets aided in determining which combination of covariates was optimal.

## DISCUSSION

### Map Results

#### Kriging vs. Cokriging

In general, a visual variance existed between the kriged and cokriged maps. The cokriged maps exhibited more

short-range variation and local detail in their depiction of the variability of the three plant parameters. However, both methods resulted in similar patterns of variability for the plant parameters. Comparable results have been found in the soil literature for topsoil silt cokriged with subsoil silt and sand as covariates (McBratney and Webster, 1983a),  $\text{NaHCO}_3$ -extractable P cokriged with 25% HCl-extractable P (Trangmar et al., 1986), and  $\text{NO}_3$  cokriged with soil EC (Zhang et al., 1992). Improved local detail of the cokriging maps was due to the finer sampling grid of the covariate(s), canopy reflectance (McBratney and Webster, 1983a). Representative maps of these observations are shown in Fig. 3. The actual differences resulting from these visual variances will be analyzed quantitatively.

#### Sampling Scheme Comparison

On the basis of the design and results of this experiment, it cannot be concluded which of the three sampling schemes is optimal for producing accurate maps of variability for vegetative characteristics. Each of the schemes used in this study was just one depiction of a

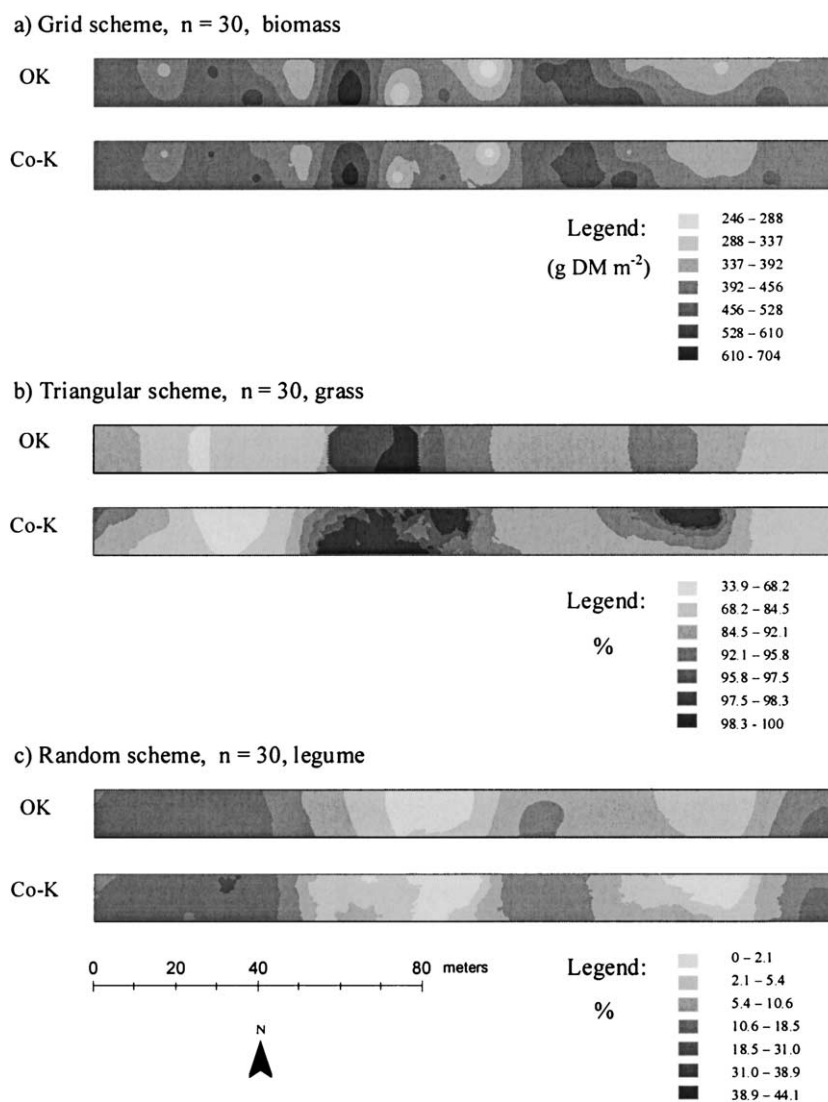


Fig. 3. Representative comparisons of kriged (OK) and cokriged (Co-K) maps for a)  $n = 30$  grid sampling scheme, biomass, b)  $n = 30$  triangular sampling scheme, percentage of grass and c)  $n = 30$  random sampling scheme, percentage of legume.

grid scheme or a triangular scheme or a random scheme in the pasture. Multiple scenarios of each scheme should be analyzed further to answer this question. General conclusions about the sampling schemes will be discussed after examining them quantitatively.

## Quantitative Results

### Kriging vs. Cokriging

When comparing results estimated with kriging and cokriging, two parameters were analyzed. Root mean square error of prediction and the correlation between predicted values from kriging and the actual values taken from direct plant measurements were evaluated. As previously mentioned, validation sets of 86 sample points were available for the  $n = 30$  sampling schemes. The RMSE should be small for an unbiased and precise prediction. As shown in Table 3, RMSE for cokriging was consistently lower than the RMSE for kriging, with one exception. Thus, cokriging helped improve the prediction of the validation sites in all the scenarios but one. The single exception occurred for biomass sampled with the random scheme. This result may be explained by the large nugget variance of biomass. Nugget variance refers to the variance associated with two measurements located at the same point. In other words, if two measurements are located at the same point (i.e., have a separation distance of zero), one would expect them to have very similar values, or zero variance. Measurements of biomass taken close to one another were quite different; thus, nugget variance resulted and the semi-variogram could not be modeled very well. In addition, the correlation of biomass with its covariate, NDVI1 ( $r = 0.43$ ), was not highly significant. Furthermore, a random sampling scheme often has "gaps" of unsampled space, so the prediction of biomass values was more reliant on the variability in neighboring covariate points than farther away biomass points. Cokriging reduced RMSE for biomass by approximately  $50 \text{ kg ha}^{-1}$  in the grid sampling scheme (Table 3). While the economic impact of this result was not studied, it is worthwhile to note.

Regression analyses between predicted and actual values showed an increase in correlation for most of the plant variables and sampling schemes when cokriging was implemented (Table 3). On the basis of the increase in RMSE with cokriging biomass in the random scheme, the decrease in correlation between predicted and actual values was not surprising. The correlation between pre-

dicted and actual values also decreased with cokriging biomass in the triangular scheme. However, the very low correlation between predicted and actual values for kriging biomass in the triangular scheme indicated that the spatial autocorrelation was difficult to model. When the target variable has a high nugget variance, gains from cokriging are not likely (Webster and Oliver, 2001).

Figure 4 illustrates the reduction in RMSE of prediction due to cokriging as a function of the absolute correlation between the reflectance covariates and the three target plant parameters. Several important observations can be made from this figure. First, a higher correlation between the target plant variable and canopy reflectance wavebands did not consistently improve reduction in RMSE. Yates and Warrick (1987) found that a reduction in kriging variance was observed as the correlation between the target variable and covariate increased. However, in this study, two covariates were used to predict percentage of grass cover and three covariates were used to predict percentage of legume cover. For the grid and the random sampling schemes, it appears that use of multiple covariates resulted in larger reductions in RMSE. This result concurred with McBratney and Webster's observation that using two covariates resulted in more precise cokriging estimations than a single covariate (McBratney and Webster, 1983a).

General trends can be drawn from Fig. 4, but it is important to note that the efficacy of cokriging is more than a function of correlation between a covariate and target variable. The efficacy also includes the strength of the spatial cross-correlation between the covariate and target variable, the geometric sampling pattern, and the ratio of the sampling intensities of the covariate to the target variable (McBratney and Webster, 1983a).

It is also possible to assess other parameters indicative of vegetative quality by spectral reflectance. Assessment of nutritive parameters such as nitrogen and lignin concentration by multispectral reflectance was examined by Serrano et al. (2002). Using Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) reflectance in chaparral vegetation, a Normalized Difference Nitrogen Index and Normalized Difference Lignin Index were proposed as indices to assess N and lignin in native shrub vegetation (Serrano et al., 2002). Canopy N concentration of eight crop fields in Denmark during the vegetative period was significantly correlated with the spectral reflectance in the green and far-red wavebands (Boegh et al., 2002).

**Table 3. Validation set root mean square errors (RMSE) of plant data prediction for kriging and cokriging the three sampling schemes. Coefficient of determination ( $r^2$ ) between predicted and actual values for validation set.**

Target variable	Sample size		Grid		Triangular		Random	
			OK†	Co-K	OK	Co-K	OK	Co-K
Biomass, g DM m <sup>-2</sup>	30	RMSE‡	81.8	76.8 (–)§	93.2	89.5 (–)	92.0	95.2 (+)
		$r^2$	0.23	0.26 (+)	0.08	0.06 (–)	0.07	0.02 (–)
Grass, %	30	RMSE	14.1	13.0 (–)	13.3	13.0 (–)	14.2	14.1 (–)
		$r^2$	0.32	0.43 (+)	0.34	0.37 (+)	0.30	0.31 (+)
Legume, %	30	RMSE	13.9	12.8 (–)	12.8	12.7 (–)	13.4	12.8 (–)
		$r^2$	0.32	0.42 (+)	0.37	0.38 (+)	0.39	0.43 (+)

† OK is ordinary kriging, Co-K is cokriging.

‡ RMSE units are specific to each plant variable.

§ Plus or minus sign in parentheses indicates an increase (+) or decrease (–) in RMSE or  $r^2$  value between OK and Co-K.

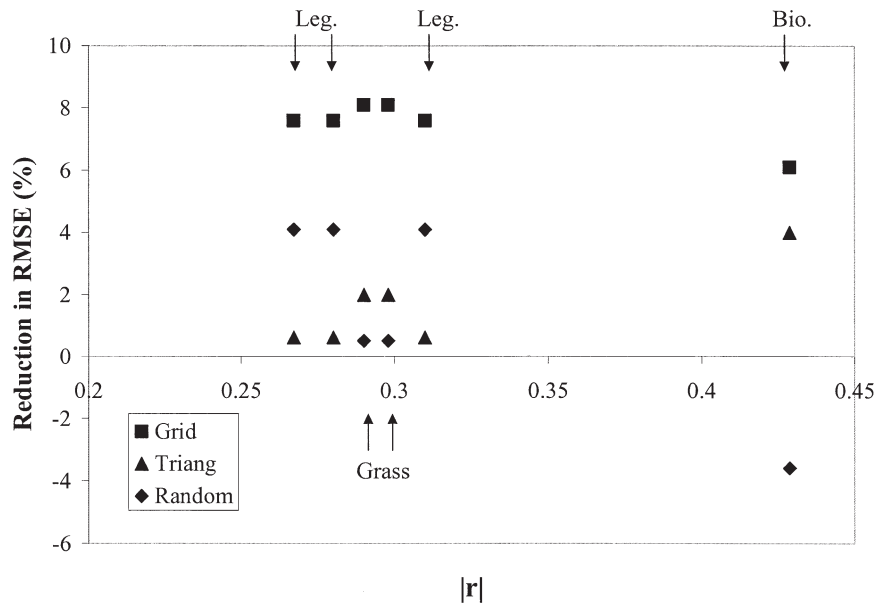


Fig. 4. Reduction in root mean square error (RMSE) of prediction due to cokriging as a function of the absolute correlation ( $r$ ) between canopy reflectance at covariate wavebands and the three target plant variables: biomass (Bio.), percentage of grass (Grass), and percentage of legume (Leg.). Data is plotted for each sampling pattern.

### Sampling Scheme Comparison

The mapping accuracy from cokriging was also affected by the sampling pattern used. Also from Fig. 4, it is evident that the largest reductions in RMSE because of cokriging were found with the grid sampling scheme. This result is probably due to the more systematic, geometric sampling of the grid scheme. Both Vauclin et al. (1983) and McBratney and Webster (1983a) found that cokriging consistently reduced estimation variances where target and covariate properties were sampled in geometric patterns. However, because only one example of each sampling scheme was used, generalizations about each of the schemes cannot be made.

### CONCLUSIONS

The results of this experiment indicate that use of rapid and indirect methods for quantifying pasture variability could provide useful and convenient information for more precise pasture management. Ground-based radiometers provide a rapidly, densely, noninvasively, and easily collected method for quantifying plant variability. The use of NDVI as a covariate improved estimation accuracy of pasture biomass when a grid sampling scheme was used. This result could ensure more accurate estimates of pasture-wide productivity. Species composition is an indication of pasture quality. This study showed that using waveband spectra as covariates can also lead to more accurate estimation of pasture composition. Thus, use of spectral reflectance as a covariate indirectly improved estimation of pasture quantity and quality.

Use of a surrogate measure such as plant canopy reflectance can be beneficial in predicting unsampled areas of a pasture. Maps resulting from cokriging reflectance values with biomass, percentage of grass cover, and percentage of legume cover exhibited more local

detail than the kriged maps of each plant parameter. The use of canopy reflectance as a covariate improved prediction of grass and legume percentage of cover in all three sampling schemes studied. The prediction of above-ground biomass was not quite as consistent; however, this was probably due to the low amount of spatial continuity of biomass values.

This study showed an overall improvement in RMSE of unsampled sites when cokriging was implemented. The grid sampling scheme appeared to benefit most from cokriging, but the results are inconclusive because only one grid scheme (not multiple) was analyzed.

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